

# Dynamic Mechanism Design for Markets with Strategic Resources

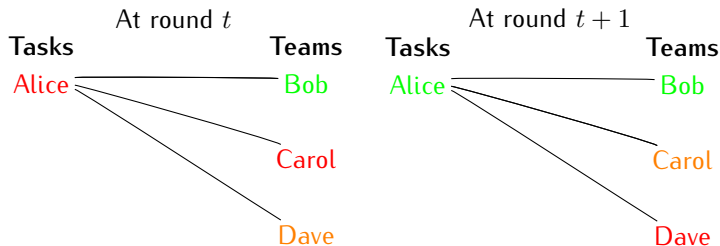
Swaprava Nath<sup>1</sup> Onno Zoeter<sup>2</sup> Yadati Narahari<sup>1</sup> Chris Dance<sup>2</sup>

<sup>1</sup> Indian Institute of Science, Bangalore    <sup>2</sup> Xerox Research Centre Europe

Conference on Uncertainty in Artificial Intelligence

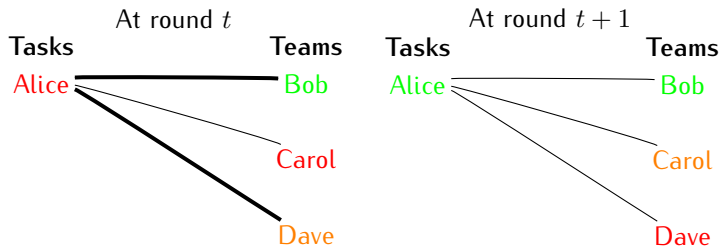
July 15, 2011

# Markets with Strategic Resources: An Example



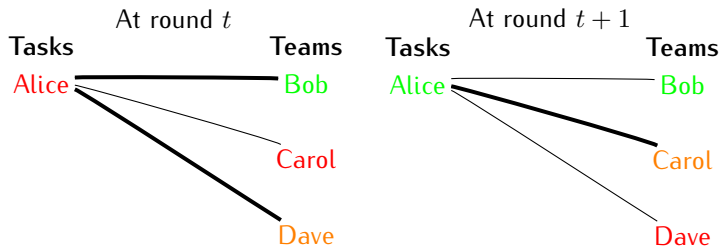
- ▶ Task difficulties (Low, Medium, High) and team efficiencies (Low, Medium, High) follow Markov chain.
- ▶ Task for central planner: assign teams to tasks in each round, balancing completed task rewards, costs, and future efficiency levels.
- ▶ If difficulties and efficiencies are known to planner, this is a Markov decision problem (MDP).

# Markets with Strategic Resources: An Example



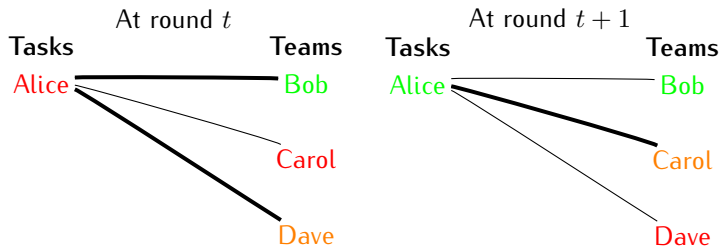
- ▶ Task difficulties (Low, Medium, High) and team efficiencies (Low, Medium, High) follow Markov chain.
- ▶ Task for central planner: assign teams to tasks in each round, balancing completed task rewards, costs, and future efficiency levels.
- ▶ If difficulties and efficiencies are known to planner, this is a Markov decision problem (MDP).

# Markets with Strategic Resources: An Example



- ▶ Task difficulties (Low, Medium, High) and team efficiencies (Low, Medium, High) follow Markov chain.
- ▶ Task for central planner: assign teams to tasks in each round, balancing completed task rewards, costs, and future efficiency levels.
- ▶ If difficulties and efficiencies are known to planner, this is a Markov decision problem (MDP).

# Markets with Strategic Resources: An Example



- ▶ Task difficulties (Low, Medium, High) and team efficiencies (Low, Medium, High) follow Markov chain.
- ▶ Task for central planner: assign teams to tasks in each round, balancing completed task rewards, costs, and future efficiency levels.
- ▶ If difficulties and efficiencies are known to planner, this is a Markov decision problem (MDP).

**This talk:** task difficulties and team efficiencies (elements in the state of the MDP) are *private information* of *strategic agents*: this is a *mechanism design* problem.

# MDP notation for our setting

**Agents** 0 task owner (one for ease of notation)  
 $\{1, \dots, n\} =: N$  set of resources.

**State** is concatenation of agent *types*

$$\begin{aligned}\theta_t &= (\theta_{0,t}, \theta_{1,t}, \dots, \theta_{n,t}) \\ \theta_{i,t} &: i\text{'s type, e.g. } \theta_{i,t} \in \{L, M, H\}\end{aligned}$$

**Action** is an assignment of resources to tasks

$$a_t \in 2^N \text{ for our 1 task example.}$$

**State transition function** is Markov and **independent** per agent

$$F(\theta_{t+1}|a_t, \theta_t) = \prod_i F_i(\theta_{i,t+1}|a_t, \theta_{i,t}).$$

# MDP notation for our setting: interdependent valuations

Reward function is sum of all agents' *valuations* (*social welfare*)

$$R(\theta_t, a_t) = \sum_{i=0}^n v_i(a_t, \theta_t) \text{ with}$$
$$v_0(a_t, \theta_t) \geq 0 \text{ denoting returns}$$
$$v_i(a_t, \theta_t) \leq 0 \text{ for } i > 0 \text{ denoting costs.}$$

**Note:** valuations are **dependent**, compare with  $v_i(a_t, \theta_{i,t})$ .

E.g. task owner's return depends on task difficulty *and* team strength.

# MDP goals

Consider infinite horizon problem with discount parameter  $\delta$ .

**Controller's goal** is to determine and execute optimal (static) policy  $\pi^*$

$$W^*(\theta_t) = \max_a [R(a, \theta_t) + \delta \mathbb{E}_{a, \theta_t} W^*(\theta_{t+1})] \quad (\text{maximal social welfare})$$

$$\pi^*(\theta_t) \in \arg \max_a [R(a, \theta_t) + \delta \mathbb{E}_{a, \theta_t} W^*(\theta_{t+1})] .$$



# Markets with strategic resources

In our strategic setting everything remains common knowledge, *except*  $\theta_t$ ,

$\theta_{i,t}$  is only observed by  $i$ .

We consider a *quasi-linear setting*: agents care about sum of discounted utilities:

$$\sum_{t=0}^{\infty} \delta^t u_{i,t} \quad \text{with}$$

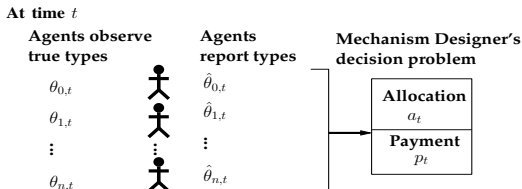
$$u_{i,t} = v_{i,t} + p_{i,t} \quad (\text{utility})$$

$$p_{i,t} > 0 \quad \text{possible } \textit{payment} \text{ from controller to agent}$$

$$p_{i,t} < 0 \quad \text{possible } \textit{payment} \text{ from agent to controller.}$$

# Mechanism designer's goals

Design a repeated game with information exchange



that achieves

**Efficiency (EFF):** mechanism yields  $W^*(\theta_t)$  under equilibrium reporting strategies.

**Truthfulness (Incentive compatibility) (EPIC):** it is optimal for  $i$  to report  $\theta_{i,t}$  truthfully when asked.

**Voluntary participation (Individual rationality) (EPIR):** agents stand to gain something from participating (non-negative utilities).

We consider (provide proofs for) *ex-post* equilibria: agent  $i$  does not make assumptions about other agent's types, but *does* assume that other agents report truthfully.

Strictly speaking *within period* *ex-post* to emphasize that agents can't foresee the future.

## Where does this work fit in?

Valuations	STATIC	DYNAMIC
Independent	<b>VCG Mechanism</b> (Vickery, 1961; Clarke, 1971; Groves, 1973)	<b>Dynamic Pivot Mechanism</b> (Bergemann and Välimäki, 2010) (Athey and Segal, 2007) (Cavallo et al., 2006)
Dependent	<b>Generalized VCG</b> (Mezzetti, 2004)	

- ▶ VCG guarantees
  - ▶ DSIC (stronger than EPIC), EFF, under certain conditions EPIR
- ▶ GVCG guarantees
  - ▶ EPIC, EFF, under certain conditions EPIR
- ▶ DPM guarantees
  - ▶ EPIC, EFF, EPIR, in non-exchange economies, budget balanced

## Where does this work fit in?

Valuations	STATIC	DYNAMIC
Independent	<b>VCG Mechanism</b> (Vickery, 1961; Clarke, 1971; Groves, 1973)	<b>Dynamic Pivot Mechanism</b> (Bergemann and Välimäki, 2010) (Athey and Segal, 2007) (Cavallo et al., 2006)
Dependent	<b>Generalized VCG</b> (Mezzetti, 2004)	<b>Generalized Dynamic Pivot Mechanism</b>

- ▶ VCG guarantees
  - ▶ DSIC (stronger than EPIC), EFF, under certain conditions EPIR
- ▶ GVCG guarantees
  - ▶ EPIC, EFF, under certain conditions EPIR
- ▶ DPM guarantees
  - ▶ EPIC, EFF, EPIR, in non-exchange economies, budget balanced
- ▶ **GDPM guarantees**
  - ▶ EPIC, EFF, EPIR, but requires more reports from agents than DPM

# The Interdependent Value Setting

- ▶ If values are dependent, *Efficiency* and *Truthfulness* cannot be guaranteed with single stage mechanisms even in static setting <sup>1</sup>
  - ▶ Without imposing any voluntary participation or budget constraints
- ▶ Need to split the decisions of allocation and payment <sup>2</sup>

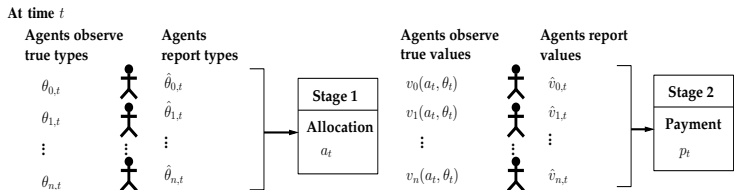
---

<sup>1</sup>P. Jehiel and B. Moldovanu. Efficient Design with Interdependent Valuations. *Econometrica*, (69):1237–1259, 2001.

<sup>2</sup>Claudio Mezzetti. Mechanism Design with Interdependent Valuations: Efficiency. *Econometrica*, 2004.

# The Interdependent Value Setting

- ▶ If values are dependent, *Efficiency* and *Truthfulness* cannot be guaranteed with single stage mechanisms even in static setting <sup>1</sup>
  - ▶ Without imposing any voluntary participation or budget constraints
- ▶ Need to split the decisions of allocation and payment <sup>2</sup>



<sup>1</sup>P. Jehiel and B. Moldovanu. Efficient Design with Interdependent Valuations. *Econometrica*, (69):1237–1259, 2001.

<sup>2</sup>Claudio Mezzetti. Mechanism Design with Interdependent Valuations: Efficiency. *Econometrica*, 2004.

# The Generalized Dynamic Pivot Mechanism (GDPM)

- ▶ The task is to design the allocation and payments on the reported types and values
- ▶ The **allocation** maximizes the social welfare taking reports as truth,

$$a^*(\hat{\theta}_t) \in \arg \max_{a_t} \mathbb{E}_{a_t, \hat{\theta}_t} \left[ \sum_{i \in N} v_i(a_t, \hat{\theta}_t) + \delta \mathbb{E}_{\theta_{t+1} | a_t, \hat{\theta}_t} W(\theta_{t+1}) \right]$$

- ▶ The **payment** to agent  $i$  at  $t$  is given by,

$$p_i^*(\hat{\theta}_t, \hat{v}_t) = \underbrace{\sum_{j \neq i} \hat{v}_{j,t} + \delta \mathbb{E}_{\theta_{t+1} | a^*(\hat{\theta}_t), \hat{\theta}_t} W_{-i}(\theta_{t+1})}_{\text{Expected discounted sum of returns to other agents, based on reported valuations and allocation for this round}} - \underbrace{W_{-i}(\hat{\theta}_t)}_{\text{Const. indep. of } \hat{\theta}_{i,t}}$$

# Main Theorem

## Theorem

*GDPM is efficient, within period ex-post incentive compatible, and within period ex-post individually rational.*

**Proof ingredients:** The allocation and payment is chosen such that

- ▶ If everyone reported true  $\theta_{i,t}$ 's, each would have got their marginal contribution,  $W(\theta_t) - W_{-i}(\theta_t)$  as the payoff (check for time instant  $t$ ).
- ▶ Goal: to show that reporting true  $\theta_{i,t}$ 's maximizes  $i$ 's payoff, given everyone else is reporting truth (EPIC).
- ▶ At  $t$ , player  $i$  cares about,
  - ▶ Current stage payoff,  $v_i(a_t, \theta_t) + p_i^*(\hat{\theta}_t, \hat{v}_t)$  and,
  - ▶ Future payoffs, i.e., the expected discounted sum of the value + payment from  $t + 1$  to  $\infty$ .
  - ▶ From time  $t + 1$ , the expected discounted sum of payoff of agent  $i$  is  $W(\theta_{t+1}) - W_{-i}(\theta_{t+1})$ , assuming agents report truthfully from  $t + 1$ .
- ▶ Putting together, agent  $i$ 's utility is,

$$v_i(a_t, \theta_t) + p_i^*(\hat{\theta}_t, \hat{v}_t) + \mathbb{E}_{\theta_{t+1}|a_t, \theta_t} (W(\theta_{t+1}) - W_{-i}(\theta_{t+1}))$$

- ▶ This is maximized at the true  $\theta_t$  reports (proved in paper).



# The use of second phase reports

## Proof ingredients:

Necessity of the second reporting phase:

- ▶ Controller can only influence assignment.

With the second reporting phase,  $i$  can only influence his payoff via the assignment, i.e. his utility is of a form

$$f(a^*(\hat{\theta}_{i,t})) .$$

Since controller optimizes what  $i$  cares about, truthfulness is optimal.

- ▶ Without second phase, payment to  $i$  would be based on

$$v_{j,t}(a_t, \hat{\theta}_{i,t}, \theta_{-i,t}) \quad (j\text{'s predicted value, based on } i\text{'s report),$$

instead of

$$\hat{v}_{j,t} \quad (j\text{'s reported value, which is independent of } i\text{'s report}).$$

What controller optimizes has form

$$f(a^*(\hat{\theta}_{i,t}), \hat{\theta}_{i,t}) ,$$

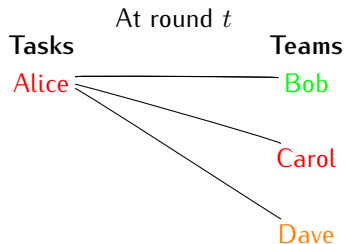
hence  $i$  has a richer optimization problem than the controller, and might strategically manipulate his report  $\hat{\theta}_{i,t}$ .

# Why care? A naïve alternative mechanism

Is obtaining efficiency straightforward?

Consider an alternative naïve mechanism

- ▶ The **allocation** maximizes the social welfare taking reports as truth.
- ▶ Task owner **pays**  $K$  to every assigned team (independent of outcome).



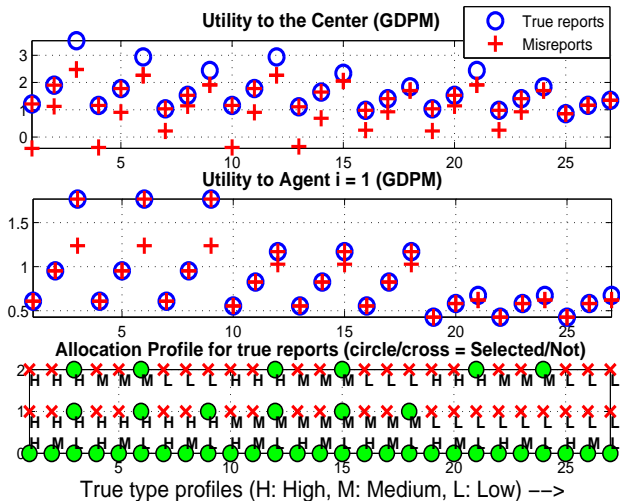
If you were Carol, would you report your low effectiveness state?

# Simulation Setting

- ▶ 3 players: 1 Task owner (Image owner), 2 Teams (Annotators)
- ▶  $\theta_{i,t} \in \{L, M, H\}$  corresponding to the difficulty/effectiveness levels for all agents:  $3^3 = 27$  possible states.
- ▶ Value structure represents law of diminishing returns.
- ▶ Transition probability matrices reflect risk of reduction in effectiveness when assigned, probability of recovery when not assigned.
- ▶ Annotators are symmetric, we need to study only one.

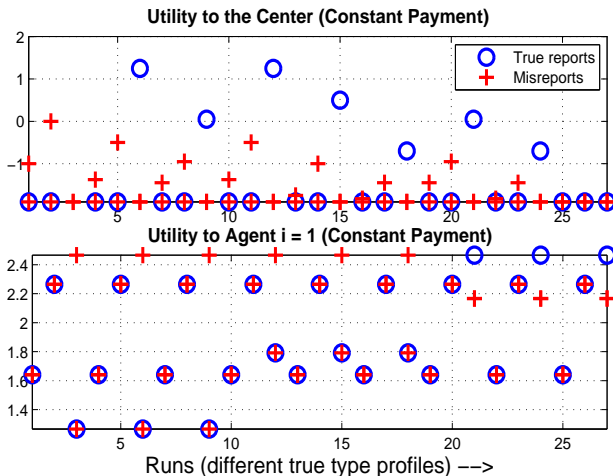
# Simulation Results

Truthfulness:



# Simulation Results (Contd.)

Comparison with a Naïve Mechanism (CONST):



# Simulation Summary

**Payment consistency (PC):** task owners only make payments, teams only receive payments.

**Budget balance (BB):** controller does not need to inject money into the exchange.

	EFF	EPIC	EPIR	PC	BB
GDPM	✓	✓	✓	×	×
CONST	×	×	×	✓	✓

- ▶ All of these properties may not be simultaneously satisfiable

# Discussion

Strategic extensions of dynamic decision problems are very important in practical problems.

We have presented a dynamic mechanism for exchange economies.

It is (within period, ex-post)

truthful, efficient, and voluntary participatory

but not

budget balanced, payment consistent

in a setting with

independent type transitions, and dependent valuations.

See also Cavallo et al. '09 who consider dynamic problems with dependent type transitions, and independent valuations.

Future work: complete this space and determine (im)possibilities.

What extra opportunities are there in the infinite discounted case over the single round setting?

Questions?